

# Statistics II Summary

Çağrı Çöltekin

University of Groningen, Dept of Information Science



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## First things first: the exam

Exam date & time: **June 21, 10:00–13:00** room: *1314.0026*.

- ▶ A mixture of multiple choice and short-answer questions.
- ▶ It should take about 90 minutes, but you can use all 3 hours reserved for the exam.
- ▶ An example exam is already on Nestor, under 'course documents'.
- ▶ You should be able to do without a calculator, but you are allowed to bring a simple calculator (without network capabilities).

# The plan of the day

A summary (with a new/different perspective at times):

Basics: hypothesis testing, statistical models.

Correlation

Regression

Multiple regression

ANOVA

Factorial ANOVA

Repeated-measures ANOVA

Logistic Regression

... some common problems & your questions.

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  - ▶ We do not stop with understanding the data, we want generalizations beyond the data at hand.
- ▶ Statistics is a collection of tools for converting data into information.



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All of these will be presented to you in some form of statistics.

# Null-hypothesis significance testing

- ▶ **Null-hypothesis significance testing** (NHST) is probably most widely used scientific tool.
- ▶ It is important to get a fair understanding of it.
- ▶ If you are confused, you are not alone. Hypothesis testing is confusing.



## Typical NHST procedure

- ▶ Define a **null hypothesis** ( $H_0$ ) that expresses when your hypothesis is wrong.
- ▶ Define an alternative hypothesis ( $H_a$ , or  $H_1$ ) as what you expect to find. (well... depending on which NHST procedure you follow.)
- ▶ Choose a significance level ( $\alpha$ -level) at which to reject the  $H_0$ . Typical values are 0.05, 0.01, 0.001.
- ▶ Apply the appropriate test, say t-test, which will yield a p-value, of obtaining the sample you have, **if  $H_0$  was true**.
- ▶ If  $p < \alpha$ , we reject the  $H_0$ , otherwise, we **fail to reject** the  $H_0$ .

## NHST: problems/suggestions

### Beware:

- ▶ The p-value is not the probability of null-hypothesis being true.
- ▶ Not finding a significant difference does not mean there is none: you can never accept the null hypothesis.
- ▶ Statistical significance does not warrant practical importance.

### Suggestions:

- ▶ Whenever you see a p-value insert 'if null hypothesis was true' in your conclusions.
- ▶ Report value of the p (not just  $p < .05$ ).
- ▶ Always look for effect sizes, interpret along with (confidence) interval estimates around the effect sizes.

## Effect sizes: what are they?

A few examples:

- ▶ The estimate of the mean.
- ▶ The estimate of the difference between two means. Or, *Cohen's d* ( $\frac{\bar{x}_1 - \bar{x}_2}{s}$ ), if you like standardized measures.
- ▶ Ratio or percentage of change (say, in a year, or after treatment).
- ▶ Correlation coefficient  $r$  (or  $r^2$ ).
- ▶ Slope values in a regression analysis.
- ▶ Proportion of variance explained by a model: multiple- $r^2$  (or adjusted- $r^2$ ),  $\eta^2$  (or  $\omega^2$ ).

It is best to interpret effect sizes with respect to the problem studied.

## Statistical models

All statistical analyses can be cast into a model:

$$\text{response} = \text{model} + \text{error}$$

- ▶ model is what we are interested in.
- ▶ error effects the precision (and certainty) of our estimates.
- ▶ we prefer models with smaller error.
- ▶ we prefer simpler models.

## What are the models?

- ▶ Model of the mean (sometime called the null model):

$$y = \mu + e$$

- ▶ Model with multiple group means (like in ANOVA):

$$y = \mu + \delta_1 + \delta_2 + e$$

- ▶ Model with a single predictor (regression, but also t-test):

$$y = a + bx + e$$

- ▶ Model with a single predictor (regression, ANOVA):

$$y = a + b_1x_1 + b_2x_2 + \dots + e$$

# Correlation

The correlation coefficient ( $r$ ) is a standardized symmetric measure of covariance between two variables.

- ▶ The correlation coefficient ranges between  $-1$  and  $1$ .
  - $-1$  perfect negative correlation:  $x$  decreases as  $y$  increase.
  - $0$  no relationship.
  - $+1$  perfect positive correlation:  $x$  increases as  $y$  increase.
- ▶ Correlation is symmetric.
- ▶ Typically between two numeric variables, but also with binary categorical variables (point biserial correlation).

## Correlation: examples

The relationship between

- ▶ Education and income.
- ▶ Height and weight.
- ▶ Age and ability (e.g., language skills, cognitive functions, eye sight, . . .)
- ▶ Speed and accuracy.
- ▶ Smoking and life expectancy.
- ▶ Time spent for work and success.

## Correlation: how to do it

- ▶ The most common correlation coefficient is **Pearson's  $r$** ,

$$r_{xy} = \frac{1}{n-1} \sum_{i=1}^n z_{x_i} z_{y_i}$$

$r$  indicates the strength and direction of the correlation.

- ▶ Inference can be based on t-distribution, the base on the statistic,

$$t = \frac{r\sqrt{n-2}}{\sqrt{1-r^2}}$$

- ▶ Assumptions are exactly like linear regression (coming soon).
- ▶ When the assumptions fail, non-parametric alternatives **Spearman's  $\rho$**  or **Kendall's  $\tau$**  can be used.



# Regression

Regression analysis is about finding the best linear equation that describes the relationship between two variables.

$$y_i = a + bx_i + e_i$$

$y$  is the *outcome* (or response, or dependent) variable. The index  $i$  represent each unit observation/measurement (sometimes called a 'case').

$x$  is the *predictor* (or explanatory, or independent) variable.

$a$  is the intercept.

$b$  is the slope of the regression line.

$a + bx$  is the *deterministic* part of the model.

$e$  is the *residual*, error, or the variation that is not accounted for by the model.

## Regression: examples

The relationship between

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- ▶ Time spent for work and success.

The same as correlation, but this time we take a 'sided' perspective.

## Regression: how to do it

Least-squares regression is the method of determining regression coefficients that minimizes the **sum of squared residuals** ( $SS_R$ ).

$$y_i = \underbrace{a + bx_i}_{\hat{y}_i} + e_i$$

## Regression: how to do it

Least-squares regression is the method of determining regression coefficients that minimizes the **sum of squared residuals** ( $SS_R$ ).

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- ▶ We try to find **a** and **b**, that minimizes the prediction error:

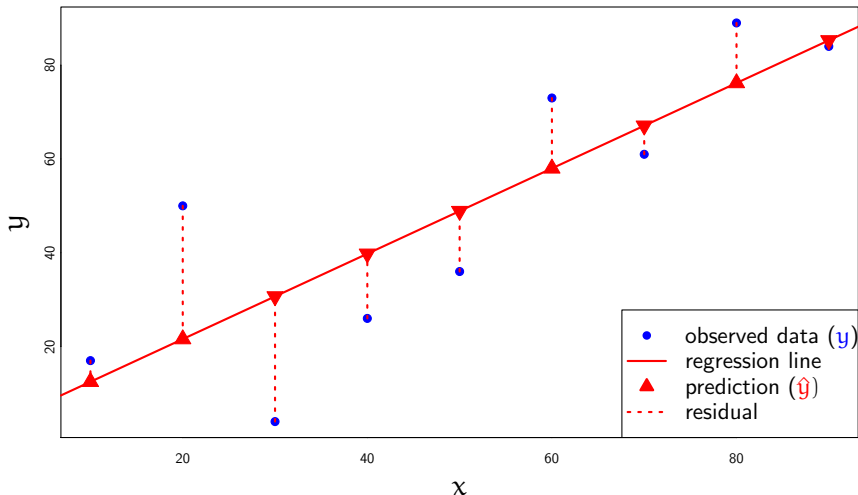
$$\sum_i e_i^2 = \sum_i (y_i - \hat{y}_i)^2 = \sum_i (y_i - (a + bx_i))^2$$

- ▶ This minimization problem can be solved analytically, yielding:

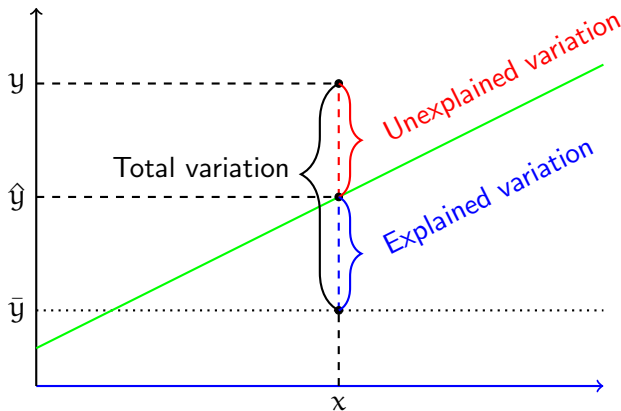
$$b = r \frac{\sigma_y}{\sigma_x}$$

$$a = \bar{y} - b\bar{x}$$

# Visualization of regression procedure



## Variation explained by regression



$$\begin{aligned}
 \text{Total variation} &= \text{Unexplained variation} + \text{Explained variation} \\
 y - \bar{y} &= y - \hat{y} + \hat{y} - \bar{y}
 \end{aligned}$$

## Regression: what to watch out for

**linearity** scatter plot of 'y vs. x' or 'residuals vs. fitted'.

**normality** (of residuals!) histogram, Q-Q (or P-P) plot.

**constant variance** (of residuals!) 'residuals vs. fitted' plot.

**outliers** scatter plot of 'y vs. x' together with regression line, residual histogram or box plot.

**influential cases** scatter plot of 'y vs. x', 'residuals vs. fitted', or more specialized statistics like *Cook's distance*.



## Regression: when things are not as expected

When things fail . . .

**independence** use more complex models (e.g., multilevel/mixed-effect models).

**linearity** transform the input or the response variable, use non-linear regression.

**normality** transform the input or the response variable, use GLMs with non-normal error.

**constant variance** transform the input or the response variable, use GLMs.

**influential cases** remove the observation (if it is a real outlier), or collect more data.

## Regression: important concepts

- ▶ Coefficient of determination

$$r^2 = \frac{\text{Explained variance}}{\text{Total variance}} = \frac{\sum_i^n (\hat{y}_i - \bar{y}_i)^2}{\sum_i^n (y_i - \bar{y}_i)^2} = \frac{SS_M}{SS_T}$$

- ▶  $r^2$  is the standardized effect size for regression. Estimates of slope(s) indicate effect sizes of individual predictors.
- ▶ Inference for the complete model is based on F distribution with  $DF = (k, n - k - 1)$

$$F = \frac{\text{Explained variance}}{\text{Unexplained variance}} = \frac{\frac{1}{k} \sum_i^n (\hat{y}_i - \bar{y}_i)^2}{\frac{1}{n-k-1} \sum_i^n (y_i - \hat{y}_i)^2} = \frac{MS_M}{MS_R}$$

for  $n$  data points and  $k$  predictors.

- ▶ Inference (confidence intervals or significance testing) for individual coefficients are performed using t-test.

# Multiple regression

$$y_i = a + \underbrace{b_1x_{1,i} + b_2x_{2,i} + \dots + b_kx_{k,i}}_{\hat{y}} + e_i$$

$a$  is the intercept (as before).

$b_{1..k}$  are the coefficients of the respective predictors.

$e$  is the error term (residual).

It is a generalization of simple regression with some additional power and complexity.

## Multiple regression: examples

- ▶ university performance dependent on general intelligence, high school grades, education of parents,...
- ▶ income dependent on years of schooling, school performance, general intelligence, income of parents,...
- ▶ level of language ability of immigrants depending on
  - ▶ leisure contact with natives
  - ▶ age at immigration
  - ▶ employment-related contact with natives
  - ▶ professional qualification
  - ▶ duration of stay
  - ▶ accommodation

## Multiple regression: issues and difficulties

Multiple regression shares all aspects/assumptions of simple regression, and

- ▶ Visual inspection of the data becomes more difficult.
- ▶ **Multicollinearity** causes problems in estimation and interpretation of multiple-regression models.
- ▶ **Suppression** is another possibility, where combination of predictors are more useful than individual predictors.
- ▶ **Overfitting**, occurs when there are large number of predictors.
- ▶ **Model selection** (finding a model that fits the
- ▶ Model fit is still measured by  $r^2$  (but, called multiple- $r^2$ ). Adjusted- $r^2$  corrects by-chance increase in multiple- $r^2$  by adding more predictors.

# ANOVA

We want to know whether there are **any** differences between the means of  $k$  groups.

- ▶ If the variance between the groups is higher than the variance within the groups, there must be a significant group effect.
- ▶ Between group variance ( $MS_{\text{between}}$ , or  $MS_M$  or  $MS_G$ ) is characterized by variance between the group means.
- ▶ Within group variance ( $MS_{\text{within}}$ , or  $MS_R$  or  $MS_E$ ) is characterized by variance of data round the group means.

Then, the statistic of interest is

$$F = \frac{MS_{\text{between}}}{MS_{\text{within}}} = \frac{MS_M}{MS_R}$$

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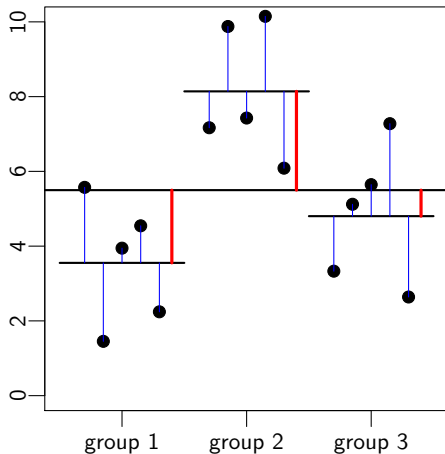
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What is the 'model' here?

## ANOVA: visualization



$$F = \frac{MS_M}{MS_R}$$

$$F = \frac{\frac{SS_M}{DF_M}}{\frac{SS_R}{DF_R}}$$

$$DF_M = k - 1$$

$$DF_R = n - k$$

where  $k$  is the number of groups, and  $n$  is the number of observations.



## ANOVA: examples

- ▶ Compare time needed for lexical recognition in
  1. healthy adults
  2. patients with Wernicke's aphasia
  3. patients with Broca's aphasia
- ▶ Effect of background color choice in a web site.
- ▶ Compare Dutch proficiency scores of second language learners based on their native language.

# ANOVA: what to watch out for

normality of response in all groups check with,

- ▶ box plots,
- ▶ histogram,
- ▶ Q-Q (or P-P) plot.

homogeneity of variance among the groups.

- ▶ Rule of thumb: no variance twice another group's variance.
- ▶ Box plots for visual inspection.
- ▶ Formal tests include 'Levene' or 'Bartlett' tests of homogeneity of variances.

## ANOVA: when things go wrong

- independence** Use repeated-measures ANOVA, or multilevel/mixed-effect linear models.
- normality** Transform the response variable, or use non-parametric Kruskal–Wallis test or more complex (linear) models.
- homogeneity of variance** Use corrected F-ratios, transform the response variable.

## Prior contrasts and post-hoc tests

- ▶ ANOVA indicates whether there are **any** differences between any pair of group means.
- ▶ A limited set of specific differences (contrasts) can be coded in ANOVA analysis.
- ▶ One can also do post-hoc tests for comparing individual group means after ANOVA analysis.
- ▶ In exploratory multiple-comparison analysis, you need to adjust your p-values (or your  $\alpha$  level), for example using Bonferroni correction.

## Factorial ANOVA

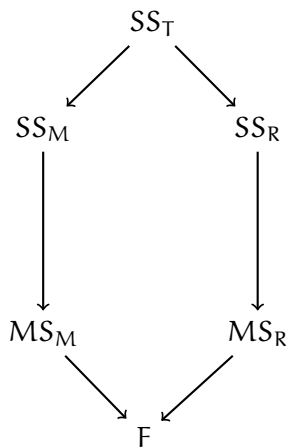
- ▶ Factorial ANOVA is a generalization of single ANOVA (or t-test).
- ▶ Compare groups along more than one dimension.
- ▶ Efficient in use of subjects.
- ▶ Allows to investigate interaction.
- ▶ Same assumptions with single ANOVA.
  - ▶ independent observations.
  - ▶ all groups are (approximately) normally distributed
  - ▶ all groups have (approximately) equal variances

## Factorial ANOVA: examples

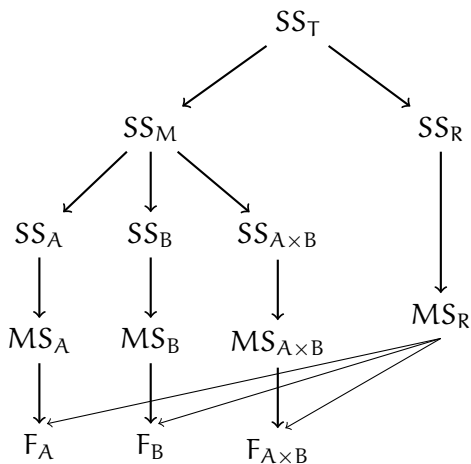
- ▶ Compare time needed for lexical recognition in
  1. healthy adults
  2. patients with Wernicke's aphasia
  3. patients with Broca's aphasiaand gender of the subject.
- ▶ Usability of an application based on different user interfaces and input methods.
- ▶ Language development of children based on their parent's education and socio-economic status.
- ▶ Compare Dutch proficiency scores of second language learners based on their native language and profession.

## Factorial ANOVA: partitioning the variance

Single ANOVA



Two-way ANOVA



## ANOVA: main effects and the interaction(s)

- ▶ For two-way ANOVA, with factors A and B,  $SS_M$  is partitioned as:

$$SS_M = \underbrace{SS_A + SS_B}_{\text{main effects}} + \underbrace{SS_{A \times B}}_{\text{interaction}}$$

- ▶ For three-way ANOVA, with factors A, B and C,  $SS_M$  is partitioned as:

$$SS_M = \underbrace{SS_A + SS_B + SS_C}_{\text{main effects}} + \underbrace{SS_{A \times B} + SS_{A \times C} + SS_{B \times C}}_{\text{2-way interactions}} + \underbrace{SS_{A \times B \times C}}_{\text{3-way inter.}}$$



## Factorial ANOVA: degrees of freedom and F-tests

As in single ANOVA:

$$\begin{aligned} DF_T &= DF_M + DF_R \\ n - 1 &= k - 1 + n - k \end{aligned}$$

If we have  $k_A$  levels due to factor A, and  $k_B$  levels due to factor B, total number of groups is  $k = k_A \times k_B$ . We can now further partition the  $DF_M$  as,

$$\begin{aligned} DF_M &= DF_A + DF_B + DF_{A \times B} \\ k - 1 &= k_A - 1 + k_B - 1 + (k_A - 1) \times (k_B - 1) \end{aligned}$$

For two-way ANOVA we get three F-tests:

$$\begin{aligned} F_A &= \frac{MS_A}{MS_R} \\ F_B &= \frac{MS_B}{MS_R} \\ F_{A \times B} &= \frac{MS_{A \times B}}{MS_R} \end{aligned}$$

## Repeated-measures ANOVA

Essentially, (factorial) ANOVA, with repeated (not independent) measurements.

- ▶ A lot more economical in experiment design.
- ▶ More powerful, since individual variation is not a problem for RM ANOVA.
- ▶ A generalization of paired t-test to multiple groups.

Repeated measures can be,

**over time:** testing effects of treatment, teaching method or just time. Typically you get more than two pre-tests or post-tests.

**not time related.** Examples:

- ▶ reaction time for different sort of stimuli
- ▶ measurements taken in the same city/region/country

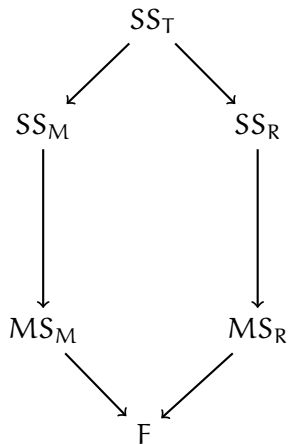
## RM ANOVA: Between subjects and within subjects variance

- ▶ A **between subjects** variance is the variation you observe due to differences between individuals.
- ▶ In independent (single or factorial) ANOVA, all variation observed is between subjects.
- ▶ A **within subjects** variation is due to variation observed in repeated measurement over the same subject.
- ▶ In a purely repeated design ANOVA, all experimental effect is confined in within-subjects variance.

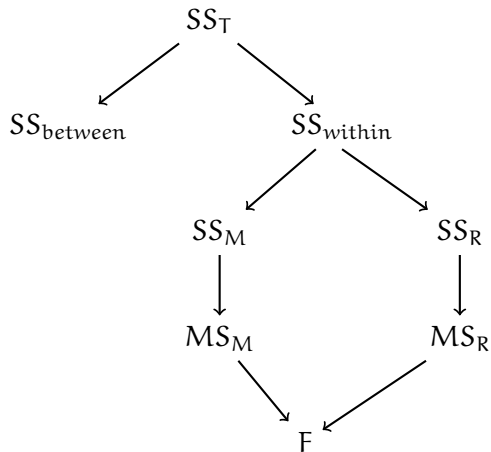
Note: measures do not have to be repeated over 'subjects', can be other 'items' present in the experimental setup.

## RM ANOVA: Partitioning the variance

Single ANOVA

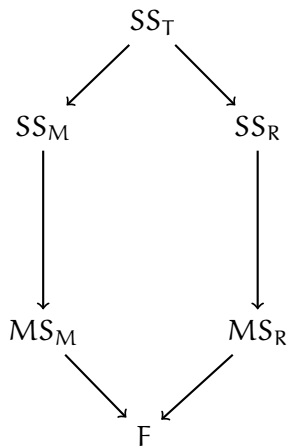


Repeated Measures ANOVA

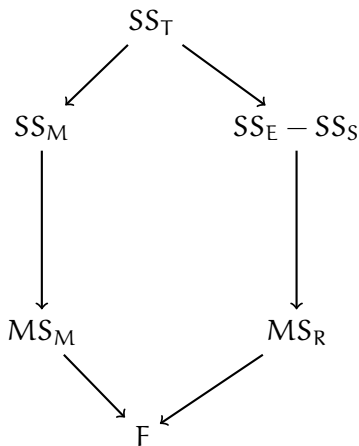


## RM ANOVA: partitioning the variance (2)

Single ANOVA



Repeated Measures ANOVA



# RM ANOVA: what to watch out for

- ▶ Assumptions
  - ▶ Normality of response variable in all experimental conditions.
  - ▶ Sphericity: homogeneity of variances of all pairwise differences.
- ▶ RM ANOVA is very sensitive to unbalanced designs, missing values.
- ▶ Carry-over effects (e.g., learning or fatigue) in experiment sequence.

## RM ANOVA: when things fail

**normality** transformation or more complex models (generalized linear multilevel/mixed-effect models) may help.

**sphericity** use adjusted F-values or again complex models (generalized linear multilevel/mixed-effect models) may help.

**unbalanced data** generalized linear multilevel/mixed-effect models, or recollect your data more carefully.

**carryover effects** randomize the order of stimuli during the experiment, or switch to between-subjects designs, do multiple experiments.

## ANOVA and effect size

▶ ANOVA as a model view:

- ▶  $\eta^2$  (=  $r^2$ , same calculation, same interpretation, just different name).

$$\eta^2 = \frac{\text{Explained variance}}{\text{Total variance}} = \frac{SS_M}{SS_T}$$

- ▶ partial- $\eta^2$  in factorial ANOVA gives variance explained by each factor (or interaction term).
  - ▶ Analogous to adjusted- $r^2$ ,  $\omega^2$  is adjusts for by-chance increase in  $\eta^2$ . Use/report (partial-) $\omega^2$  when you can.
- ▶ ANOVA as hypothesis testing method:
- ▶ Mean differences (or Cohen's d) in pairwise comparisons.
  - ▶ Coefficients of contrasts.



# Logistic regression

Logistic regression is an extension of regression (or a case of generalized linear models) where response variable is binary.

Two important differences:

- ▶ Transform the response variable so that estimated values are between 0 and 1.
- ▶ Allow non-normal residuals.

$$\underbrace{\text{logit}(p_i)}_{\log \frac{p}{1-p}} = a + b_1 x_{1,i} + \dots + b_k x_{k,i} + e_i$$

## Logistic regression: examples

- ▶ survival after a surgery depending on age, length of surgery, ...
- ▶ whether purchase occurs depending on age, income, website characteristics, ...
- ▶ whether speech errors occur depending on alcohol level
- ▶ when linguistic rules apply (final [t] in Dutch) depending on speed of utterance, stress, social group, ...
- ▶ whether one votes to a political party (or not) depending on age, income, ethnicity, ...

## Logistic regression: estimation

- ▶ Maximum likelihood estimation (MLE) tries to find the set of model parameters, or coefficients,  $\alpha$ ,  $b_1, \dots, b_k$ , which make the data most likely (or minimize the error).
- ▶ MLE is an iterative search for the optimum parameter values. There is no exact solution.
- ▶ In some cases, MLE may fail to find a solution.
- ▶ If errors are normally distributed, MLE is equivalent to least-squares estimation.
- ▶ With MLE,  $r^2$  is not the measure of model fit. Instead we use deviance =  $-2\text{LogLikelihood}$  to measure model fit (lower, better).
- ▶ Unlike  $r^2$ , deviance is not comparable for models fit on different data.

## Logistic regression: what to watch out for

- ▶ Binomial response = non-normal errors.
- ▶ Overdispersion: when variance diverges from what is expected in binomial data.
- ▶ Linear relationship between logit transformed response and predictors.
- ▶ MLE related: MLE may fail to find a good fit. In case of
  - ▶ complete separation.
  - ▶ unevenly distributed data points.
- ▶ Otherwise the same as multiple regression.

# Logistic regression: when things fail

**overdispersion** GLMs with quasi-binomial error.

**MLE fails** Collect more data, or use Bayesian estimation.

**independence** Same as regression: multilevel (generalized) linear models.

**linearity** Same as regression: transform predictor/response or use non-linear regression.

## Least-squares estimation

Quiz 1, Question 9 (6.7 average).

Least-squares regression equation is determined by minimizing the square of the

- A. differences between observed  $y$  values and predicted  $y$  values.
- B. differences between observed  $x$  values and predicted  $x$  values.
- C. distance between the regression line and the observed data point.
- D. correlation coefficient.

## Correlation and variance explained

Quiz 1, Question 4 (6.5 average).

A researcher finds a correlation of  $r=0.4$  between IQ and creativity scores. What percentage of the variance in creativity scores is **not** explained by the IQ?

- A. 40%
- B. 60%
- C. 84%
- D. 16%

## $r^2$ from sums of squares

Quiz 2, Question 9 (3.5 average).

For a linear regression model, total variance of the response variable,  $SS_T = 2500$  and residual sum of squares,  $SS_R = 500$ . Find the multiple- $r^2$ .



## F-ratio from sums of squares

Quiz 3, Question 4 (3.0 average).

In an ANOVA with six groups and 10 participants in each group, between group sum of squares,  $SS_M = 55$  and within group sum of squares,  $SS_R = 108$ . What is the F value?

## Interaction terms in a 4-way ANOVA

Quiz 4, Question 7 (1.4 average).

What is the number of interaction terms in a 4-way ANOVA?

## RM ANOVA number of subjects

Quiz 5, Question 3 (0.8 average).

A researcher reports a repeated-measures ANOVA F-value with  $df = 2,40$ . How many subjects participated in the experiment?